Commun Nonlinear Sci Numer Simulat 29 (2015) 346–358

Contents lists available at ScienceDirect

Commun Nonlinear Sci Numer Simulat

journal homepage: www.elsevier.com/locate/cnsns

Adaptive stochastic resonance in self-organized small-world neuronal networks with time delay

Haitao Yu*, Xinmeng Guo, Jiang Wang, Chen Liu, Bin Deng, Xile Wei

School of Electrical Engineering and Automation, Tianjin University, Tianjin, 300072, P. R. China

ARTICLE INFO

Article history:
Received 3 November 2014
Revised 16 April 2015
Accepted 15 May 2015
Available online 27 May 2015

Keywords:
Spike-timing-dependent plasticity
Time delay
Adaptive stochastic resonance
Neuronal network
Small-world

ABSTRACT

In this paper, adaptive stochastic resonance in time-delayed Newman–Watts small-world neuronal networks is studied, where the strength of synaptic connections between neurons is adaptively modulated by spike-timing-dependent plasticity (STDP). Numerical results show that, in the absence of information transmission delay, the phenomenon of stochastic resonance occurs and the efficiency of networked stochastic resonance can be slightly depressed by STDP. Due to the reduction of strong couplings induced by STDP, for a larger adjusting rate of STDP, a smaller peak value of the resonance response is obtained. In addition, the effect of stochastic resonance can be either promoted or destroyed by time delay, and multiple stochastic resonances appear intermittently at the integer multiples of periods of the subthreshold forcing. Furthermore, it is demonstrated that the networked stochastic resonance can also be dramatically affected by the small-world topology. For small and moderate adjusting rate of STDP, fine-tuning of the probability of adding links can significantly enhance the effect of stochastic resonance in adaptive neural network. Additionally, there is an optimal probability of adding links by which the noise-induced transmission of weak periodic signal peaks and the location of this span depends largely on the time delay and adjusting rate.

1. Introduction

Noise can emerge as a constructive component of nonlinear systems [1–3]. One important representative of this fact is stochastic resonance (SR), which occurs when the response of a nonlinear dynamical system to a weak periodic signal is optimized by moderate intensity of random fluctuations [4–7]. Recently, SR has sparked growing interest both in theoretical models of neural systems and in experimental neuroscience [8–10]. It is shown that the ability of sensory neurons to process weak input signals can be significantly enhanced by adding noise to the system [11,12]. Additionally, statistical signal processing in coupled neural systems improves with the aid of various levels of stochastic noise via SR [13,14]. Therefore, the study of stochastic resonance is valuable for understanding the signal transmission and information propagation in neuronal networks.

The last decade has growing body of modelling work on stochastic resonance in complex neuronal networks, especially in scale-free networks [15,16] and small-world neuronal networks [17–19]. Perc studied stochastic resonance on weakly paced scale-free networks and indicated that, all the features of the placement of the pacemaker, coupling strength and the inhomogeneous structure of scale-free networks play a crucial role in SR [15]. On the other hand, the effect of SR on excitable small-world networks can be amplified only for intermediate coupling strengths in excitable networks via pacemaker [18]. The study on

---

* Corresponding author. Tel.: 86 22 27402293.
E-mail address: htyu@tju.edu.cn (H. Yu).

http://dx.doi.org/10.1016/j.cnsns.2015.05.017
1007-5704/© 2015 Elsevier B.V. All rights reserved.

stochastic resonance in Newman–Watts small-world also demonstrates that fine-tuning of the small-world network structure can largely enhance the stochastic resonance in neuronal networks [20].

Time delay, which occurs due to the finite speed of action potentials propagating across neuron axons and finite reaction times for dendritic and synaptic processing, is an important fundamental feature of the nervous system [21]. In recent years, much attention has been focused on the various dynamical phenomena in time-delayed neural systems [22–24]. For example, Wang and his colleagues have extensively studied the effects of information transmission delays on the synchronization transitions in complex neuronal networks [25–27]. It is shown that fine-tuned information transmission delays are vital for assuring optimally synchronized excitatory fronts on complex neuronal networks [25]. Moreover, resonance, as an indispensable part of neural dynamics, has also been widely investigated in delay-induced systems [28–30]. Researchers explored the SR in scale-free neuronal networks with transmission delay and found that multiple stochastic resonances can be induced by appropriately tuned delays irrespective to the placing of the subthreshold periodic pacemaker [31].

However, most of the previous studies of stochastic resonance on complex neuronal networks were devoted to a static description of synaptic connectivity, while in reality the synaptic strength varies as a function of neuromodulation and time-dependent processes. One important form of these biological synaptic processes is spike-timing-dependent plasticity (STDP), which modulates the coupling strength adaptively based on the relative timing between pre- and post-synaptic action potentials [32,33]. A series of biological works have confirmed the existence of STDP, which commonly occurs at excitatory synapses onto neocortical [34] and hippocampal pyramidal neurons [33], excitatory neurons in auditory brainstem [35], parvalbumin-expressing fast-spiking striatal interneurons [36], etc. Experimental researches show that the functional structures in the brain can be remapped through STDP, which is prevalently reorganized into both small-world and scale-free networks [37,38]. More recently, modelling studies on functional role of STDP in neural dynamics have gained increasing interest [39–41]. For example, Lee et al. use a simplified biophysical model of a cortical network with STDP, which provides a mechanism for potentiation and depression depending on input frequency, and suggest that the slow NMDAR current decay helps to regulate the optimal amplitude and duration of the plasticity [42]. In addition, it is reported that, STDP, which adaptively modifies strengths of synaptic connections, considerably weakens the synchronization of neuronal activity in small-world networks [43]. Furthermore, coherence resonance and stochastic resonance have also been investigated in self-organized neural network with STDP [44]. It is shown that the selectively refined connectivity modified through STDP can highly enhance the ability of neuronal communications and improve the efficiency of signal transmission in the network [45].

In the present work, the pivotal effects of time delay and STDP on stochastic resonance in small-world neuronal networks will be studied. We aim to investigate how the network connections evolve during the process refined by STDP and the dependence of SR on it. Furthermore, fundamental roles of information transmission delay and small-world structure in networked stochastic resonance will be discussed as well. The remainder of this paper is organized as follows: in Section 2, a simplified model of time-delayed small-world neuronal network is established and STDP rule is used to modify the strengths of synaptic connections between neurons. We explore the evolution of connection synapses via STDP within a noisy background in Section 3. In Section 4, the dependence of stochastic resonance on STDP, time delay, as well as small-world topology is systematically studied. Finally, a brief conclusion of this paper is drawn in Section 5.

2. Mathematical model

The FitzHugh–Nagumo (FHN) neuron model [44] is used to describe the neuronal dynamics, and the temporal evolution of each unit can be defined as follows:

$$e\frac{dV_i}{dt} = V_i - \frac{V_i^3}{3} - W_i + I_{\text{ex}} + I_i^{\text{syn}} + \sigma\xi_i, \tag{1}$$

$$\frac{dW_i}{dt} = V_i + a - b_i W_i, \tag{2}$$

where $i\,(i = 1, 2, \cdots, N)$ is the index of neurons. $V_i(t)$ represents the fast transmembrane voltage of the ith neuron, whereas $W_i(t)$ is a slow recovery variable. The small value of parameter $e\,(e = 0.08)$, which is the time scale ratio of membrane and recovery variable, guarantees that $V_i(t)$ evolves much faster than $W_i(t)$. I_{ex} stands for the external stimulus current. The Gaussian white noise ξ_i with mean 0 satisfies $\langle \xi_i(t)\xi_j(t')\rangle = \delta_{ij}\delta(t - t')$. σ denotes the intensity of the noisy background. The parameters of a and b codetermine the dynamics of a single neuron. In our simulations, the parameter a is constantly chosen as 0.7. Accordingly, the dynamics of a single neuron depends largely on the value of variable b: the neuron is excitable for $b > 0.45$; while for $b < 0.45$, it exhibits an oscillatory behaviour generating periodic spikes. Considering that the neurons in nervous system are not identical, in our study, b_i (the value of parameter b of the ith neuron) is randomly distributed in $[0.5, 0.75]$, so that all neurons within the network are of different excitability. The synaptic current I_i^{syn} is described by:

$$I_i^{\text{syn}} = -\sum_{j=1\,(j\neq i)}^{N} g_{ij}C_{ij}s_j(t)(V_i - V_{\text{syn}}), \tag{3}$$

where C_{ij} is a bidirectional connectivity matrix, if neuron j couples to neuron i, then $C_{ij} = 1$ and $C_{ji} = 1$, otherwise $C_{ij} = C_{ji} = 0$ and $C_{ii} = 0$. The type of synapse is subjected to the value of reversal potential V_{syn}, which is set to be $V_{\text{syn}} = 0$ as only excitatory